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Recession Forecasting with Dynamic Probit Models under Real Time Conditions

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Abstract

In this paper a dynamic probit model for recession forecasting under pseudo-real time is set up using a large set of macroeconomic and financial monthly indicators for Germany. Using different initial sets of explanatory variables, alternative dynamic probit specifications are obtained through an automatized general-to-specific lag selection procedure, which are then pooled in order to decrease the volatility of the estimated recession probabilities and increase their forecasting accuracy. As it is shown in the paper, this procedure does not only feature good in-sample forecast statistics, but has also good out-of-sample performance, as pseudo-real time evaluation exercises show.

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Keywords: Dynamic probit models, out-of-sample forecasting, yield curve, real-time econometrics

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1 Introduction

Due to its great relevance for the proper design and conduct of an anticyclical economic policy, the accurate prediction of turning points in the business cycle under real time is one of the most important aspects of macroeconomic forecasting. This task is, however, also one of the most challenging, not only due to the many potential nonlinearities at work at the onset of a turning point in economic activity, but also due to the significant degree of uncertainty of macroeconomic data at the end-point, among other things.

In order to better understand the determinants of the occurrence of up- and downturns in the level of economic activity, since the seminal contribution by Burns and Mitchell (1946) the ability of numerous macroeconomic and financial variables to predict future business cycle developments has been investigated by means of a variety of parametric and nonparametric econometric techniques over the years. Following especially the work by Harvey (1989), Stock and Watson (1989), Estrella and Hardouvelis (1991), and Bernanke (1990) a great amount of this research has focused on the role of financial variables, and especially of the yield curve, i.e. the spread between long- and short-term yield of public securities, in the prediction of prospective economic recessions (economic turning points), see e.g. Estrella and Mishkin (1998), Bernand and Gerlach (1998), Estrella, Rodriguez and Schich (2003), and Moneta (2005), Wright (2006), Haltmeier (2008), and Rudebusch and Williams (2009), among others.

On practical grounds and more particularly with regard to the real time forecasting of business cycles developments, the use of financial variables – provided they have at least a predictive power as good as that of other alternative macroeconomic variables – is more advantageous, as financial time series are more timely available and are normally not subject to ex-post revisions. These considerations are not trivial: Since real economy indicators are subject to significant information lags and revisions (Rudebusch and Williams (2009) e.g. point out that the final estimates of U.S. quarterly GDP figures are only available about three months after the end of each quarter), when developers of econometric forecasting models evaluate them on the basis of the latest available vintage, they do not acknowledge the fact that their models may generate much worse forecasts in real time than with the latest available data, as recently stressed by Stark and Croushore (2002).

The main contribution of this paper to the literature on real time recession forecasting is the development of a dynamic probit indicator along the lines of recent studies on recession forecasting using binary response models such as Kauppi and Saikonnen (2008) and Nyberg (2009) based (primarily) on financial time series, as well as on macroeconomic time series less prone to data revisions, for recession forecasting under real time conditions on a monthly basis. As it will be discussed in this paper, through the estimation of a variety of alternative dynamic probit regressions underlying yield spreads of different maturities and the averaging of the resulting recession probability estimates not only a great deal of information of the term structure is taken into consideration, but also a lower volatility of the recession forecast is achieved.

The remainder of this paper is organized as follows. In section 2 the recent literature on business cycle turning point selection and recession forecasting is overviewed. Previous research on recession forecasting using binary response models is discussed in section 3 with a special focus on their real time implementability. The specific modeling of an econometric forecasting tool based on the dynamic binary response approach for recession forecasting in Germany is discussed in section 4. Finally, section 5 draws some conclusions from this study and points out possible extensions left for future research.

2 Business Cycle Turning Points Detection and Recession Forecasting: A Brief and Selective Overview of the Literature

In one of the earliest accounts of the characteristics of business cycles, Burns and Mitchell (1946, p.3) defined an economic recession as "a substantial prolonged decline in economy activity that occurs broadly across various sectors of the economy", see also Lucas (1977). This definition, though somewhat vague, summarizes in a good manner three fundamental aspects of an economic recession: the severity of the economic downturn, its non-trivial minimum duration and its broad impact across the economy.

Ever since, this general notion of the main characteristics of a recession has coined the following research: For instance, the probably most widely accepted definition of a recession, namely the one delivered by the NBER Business Cycle Dating Committee, is also oriented to a largely synchronized comovement of a selected set of macroeconomic variables which are supposed to deliver a broad account of the whole economy's development, or, in the NBER's own words:[1]

[1] For a a detailed chronology of the U.S. business cycles by the NBER Business Cycle Dating Committee, see `http://www.nber.org/cycles.html`.

> A recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. A recession begins just after the economy reaches a peak of activity and ends as the economy reaches its trough. Between trough and peak, the economy is in an expansion.

Based on the Burns and Mitchell (1946) characterization of recessions, a great amount of research on the accurate detection and prediction of turning points in the business cycle has been undertaken along the years using a variety of statistical and rather descriptive methods, as well as parametric and non-parametric econometric tools. A possible, but by no means exclusive, way to classify the different detection approaches is through the differentiation between *observational* and *implicit* detection of business cycle turning points. The *observational* approach – pioneered by the seminal contribution of Bry and Boschan (1971) and further extended to a multivariate approach by Harding and Pagan (2002), characterizes the occurrence of business cycle turning points on the basis of certain *observable* patterns of one or more business cycle reference series.[2] In contrast, the underlying notion of *implicit* approach pioneered – from different perspectives – by the work of Neftci (1982) and Hamilton (1989) is that economic expansions and recessions are generated by different *unobservable* variables or states which can only be identified in an indirect manner. More specifically, for instance in Hamilton's (1989) original contribution, the underlying data generating process (DGP) of the business cycle is modeled as being driven by stochastic and unobservable regimes or "states" linked by a Markov-Chain which jointly generate the growth rate of real output Δy_t:

$$\Delta y_t - \mu(s_t) = \alpha_1(\Delta y_{t-1} - \mu(s_{t-1})) + \ldots + \alpha_4(\Delta y_{t-4} - \mu(s_{t-4})) + u_t, \tag{1}$$

where μ is the mean growth rate of output in the "regime" s_t (with $\mu_1 < 0$ in the 'recession' regime and $0 < \mu_2$ in the 'expansion' regime), and $u_t \sim NID(0, \sigma^2)$, assumed to be the same in both regimes. Because both regimes are unobservable, only the estimation of the *probability* of the economy of being in a determined regime s in a period t can be achieved.

Furthermore, another research strain which gathers both the *observational* and the *implicit* approach to business cycle dating is the literature on dynamic factor models based on the work by Sargent and Sims (1977), Geweke (1977), and Stock and Watson (1989). According to this literature, the comovements of all leads and lags among coincident busi-

[2] See Anas, Billio, Ferrara and Mazzi (2008) for a more recent contribution along this line of research.

ness cycle reference series gathered in a vector $\mathbf{y_t}$ are modeled as arising from a single common source c_t, which is an unobservable time series which can be thought of as the overall state of the economy. In Stock and Watson (1993), for example, analogously to the Bry and Boschan (1971) approach a recession is identified if Δc_t falls below a threshold $\mathfrak{T}_\mathbf{t}$ for a certain number of consecutive months.

However, while most of these dating approaches – as well as many other not mentioned here – seem to perform quite well in the ex-post detection of business cycles turning points, see e.g. Chauvet and Piger (2005), the great majority of these methods is not applicable in the context of real-time forecasting. Concerning most non-parametric approaches along the lines of Bry and Boschan (1971) and Harding and Pagan (2002), for example, the identification of a turning point in the business cycle can only occur with a significant delay, as in most of these procedures both lags *and* leads of the reference variables are needed. So while the assessment of business cycles can be unproblematically undertaken ex-post, at the actual end-point such an assessment is not possible to undertake. Analogously, the NBER definition has significant disadvantages related to the recognition of business cycles turning points in real time, since real GDP figures are only available on a quarterly basis and are subject to non-trivial revisions, the recognition of turning points can only occur ex-post and with a significant delay. These issues, however, do not imply that such non-parametric approaches are not useful for the out-of-sample forecasting of business cycles and their turning points under real-time conditions. Through the identification of the different business cycle phases on the basis of clearly defined and economics-based rules, these non-parametric approaches can generate for instance economically meaningful binary series which can in turn be used as left-hand side variables in binary choice models. This is the direction pursued in the remainder of this paper.

3 Dynamic Probit Models and Real-Time Forecasting

As previously mentioned, following the work by Estrella and Hardouvelis (1991), binary response models have been widely used for the estimation and forecasting of recessionary periods during the last twenty years, with Moneta (2005), Wright (2006), Haltmeier (2008), Kauppi and Saikonnen (2008), Rudebusch and Williams (2009) and Nyberg (2009) being among the most recent studies using this methodology. In this strain of the literature, binary recession indicator series representing the state of the economy within the business cycle b_t is set such that

$$b_t = \begin{cases} 1, & \text{if the economy goes through a recessionary phase at time } t \\ 0, & \text{if the economy experiences an expansion at time } t. \end{cases}$$

Let Ω_{t-h} be the information set available at $t-h$, where h represents the forecasting horizon. Assuming for starters a one-period ahead forecast horizon $h = 1$, if E_{t-1} and $\text{Prob}_{t-1}(\cdot)$ represent the conditional expectation and the conditional probability given the information set Ω_{t-1}, respectively, under the assumption that b_t has a Bernoulli distribution

$$b_t | \, \Omega_{t-1} \sim \mathcal{B}(p_t),$$

the conditional probability p_t that b_t takes the value 1 in t is then given by

$$E_{t-1}(b_t) = \text{Prob}_{t-1}(\, b_t = 1) = p_t = \Phi(\varphi_t).$$

where φ_t represents the linear model equation of the variables contained in the information set Ω_{t-1} and $\Phi(\cdot)$ the linking function between φ_t and the conditional probability $\text{Prob}_{t-1}(\, b_t = 1)$ according to the Bernoulli distribution, which in probit models is given by a standard normal distribution function.

Let us now focus in more detail on the elements contained in the information set Ω_{t-1} under real time conditions. For this, it is useful to define two further (lower bound) lag types relative to the end-point: the recession recognition lag r, i.e. the lag length required by the underlying turning points dating algorithm, and the data availability lag s, where $r > s$ normally holds. Using this lag length restriction, the information set underlying a $h-$period ahead forecast can be further specified as

$$\Omega_{t-h} \quad = \quad \{b_{t-j}, b_{t-j-1}, \ldots, \mathbf{x}_{t-k}, \mathbf{x}_{t-k-1}, \ldots\}, \quad \text{with } j \geq h + r, \quad k \geq h + s \qquad (2)$$

where b_{t-j} is a scalar containing the values of the binary recession indicator, and $\mathbf{x}_{t-k}$ a vector containing the set of additional explanatory variables available at t– h. The explicit specification of these two lag lower bounds constraints is by no means trivial: In contrast to an econometric analysis based on ex-post data, the conception of an econometric tool meant to forecast the occurrence of recession under real-time conditions has to take into account not only the recession recognition lag determined by the specific recession detection or dating algorithm used to create the binary recession indicator b – as the majority of such algorithms need both lags and leads of the business cycle reference series to determine the occurrence of economic turning points –, but also the data availability lag underlying most macroeconomic time series.[3]

Taking into account these real-time conditioned lag length constraints, the linear model equation of so-called "static" probit models used in early empirical studies on the forecasting of U.S. recessions such as Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) for the $h-$period ahead forecast of a recession in t is[4]

$$\varphi_t = c + \mathbf{x}'_{t-k}\,\beta \quad \text{with } k \geq h + s \tag{3}$$

The value-added of this specific formulation of these real-time conditioned lower-bound lag constraints turns out clear in the case of the "dynamic" probit specification proposed by Dueker (1997), where lagged values of the binary recession variable are included as an additional explanatory variable in order to address a possible autocorrelation of the recession binary series. Indeed, from the real-time perspective of this paper, due the recognition lag of the binary recession variable r (and the data availability lag s), only the following specification of the linear function underlying the probit model $E_{t-h}(b_t) = \Phi(\varphi_t)$ is feasible at the end-point:

$$\varphi_t = \sum_{j=h+r}^{q} \delta_j \, b_{t-j} + \mathbf{x}'_{t-k}\,\beta, \quad k \geq h + s \tag{4}$$

As this equation clearly shows, the latent misspecification problem to which the static specification – which implicitly rules out a priori any type of autocorrelation of the binary series b – is subject to can only be addressed for an autocorrelation order of higher than $h + r$ (accordingly, the longer the recession recognition lag is, the lower the ability of the model will be to account for an eventual low order autocorrelation of the binary series b). Implicitly, Dueker (1997, p.45) points out this issue as follows: "Three months is probably a minimum recognition lag time for recessions. It would clearly not be reasonable to include last month's value of the recession binary variable as an explanatory variable, because it takes more time to recognize that the economy has entered a recession. [. . .] If three months seems less than the minimum recognition lag time for recessions, then one can concentrate on the results for 6, 9 and 12 months." Accordingly, only the lagged value b_{t-h-r} can be included in Ω_{t-h} due to the binding recession recognition lag r.

[3]As it will be discussed below, the variables used in this study stemming from the Bundesbank database are available with an average lag of three months.

[4]In a strict sense, both the recession recognition and the data availability lags, as well as the very specification of a probit model in the sense of $h-$period ahead forecasting

More recently, Kauppi and Saikonnen (2008) have proposed a "dynamic autoregressive" specification, whereafter not only lagged values of the binary series b, but also those of the linear function φ_t are included in the model's specification, which for the one−period ahead forecast reads

$$\varphi_t = \sum_{i=1}^{p} \alpha_i \, \varphi_{t-i} + \sum_{j=1}^{q} \delta_j \, b_{t-j} + \mathbf{x}'_{t-1} \, \beta. \tag{5}$$

As discussed in Nyberg (2009), it can be shown by recursive substitution of the special case $\varphi_t = \alpha_1 \varphi_{t-1} + x_{t-k}\beta'$ that the dynamic autoregressive model described by eq.(5) is

$$\varphi_t = \delta_1 \sum_{i=1}^{\infty} \alpha_1^{i-1} b_{t-i} + \sum_{i=1}^{\infty} \alpha_1^{i-1} \mathbf{x}'_{t-i} \, \beta, \tag{6}$$

an "infinite" order extension of the dynamic probit model $\varphi_t = \delta_1 b_{t-1} + \mathbf{x}'_{t-1} \, \beta$.

It should be noted, however, that under the explicit consideration of the recession recognition and data availability lower-bound lag constraints, the dynamic autoregressive probit specification (assuming again $h = p = 1$ and $q = 0$ for notational simplicity) feasible under real-time conditions is

$$\varphi_t = \delta_1 \sum_{i=1+r}^{\infty} \alpha_1^{i-1-r} b_{t-i} + \sum_{i=1+s}^{\infty} \alpha_1^{i-1-s} \mathbf{x}'_{t-i} \, \beta, \tag{7}$$

or, for the more general and h−period ahead forecast case

$$\varphi_t = \sum_{i=1}^{p} \alpha_i \, \varphi_{t-i} + \sum_{j=h+r}^{q} \delta_j \, b_{t-j} + \mathbf{x}'_{t-k} \, \beta, \quad k \geq h + s. \tag{8}$$

From eq.(7) it is clear that the ability of the dynamic autoregressive specification to ad-ddress a potential low-order autocorrelation of b_t (as well as of φ_t) strongly depends on the lag lower-bound constraints r and s.

Alternatively, as normally the informational lag s is much shorter than the recession recognition lag r, a possible way to account for low-order autocorrelation of the binary recession series b_t could be to include in the model's linear equation, and thus in the information Ω_{t-h}, the vector of the underlying business cycle reference series $\mathbf{y}$ – which in the case of the NBER chronological business cycle definition comprises real GDP, real income, employment, industrial production, and wholesale-retail sales. For the case of a h−period ahead forecast, we then have

$$\varphi_t = \sum_{j=h+r}^{q} \delta_j \, b_{t-j} + \sum_{i=h+s}^{q} \mathbf{y}'_{t-i} \, \alpha_i + \sum_{j=h+s}^{q} \mathbf{x}'_{t-j} \, \beta_j. \tag{9}$$

This alternative specification can be motivated by the fact that the binary recession series is generated by a nonlinear transformation – determined by the employed turning points dating algorithm – of the business cycle reference series comprised in the vector $\mathbf{y}$.

It should be clear that the value-added of the inclusion of the vector $\mathbf{y}$ in $\varphi_t(\cdot)$ increases the larger is the difference between r and s, as the number of observations close to the end-point potentially able to explain the autoregressive structure of b_t additional to the lagged values of β_{t-j}, $j \geq h+r$ is

$$\sum_{i=r-s}^{r-1} \mathbf{y}'_{t-i}\, \alpha_i.$$

To the best of our knowledge, however, while the vector of business cycle reference series $\mathbf{y}$ can of course be included in $\mathbf{x}$, this has not been done in the majority of related studies previously mentioned. This is, among other things, one of the ways through which this paper contributes to the literature.

The following sections describe the application of alternative dynamic probit models for recession forecasting using German macroeconomic data.

4 Forecasting German Recessions under Real Time Conditions

4.1 The Dataset

For the following exercise of recession forecasting, a wide dataset of macroeconomic indicators of the German economy was employed. All financial and real economy variables stem from the Bundesbank database (`www.bundesbank.de/statistik/`), with the exception of the orders, which stem from the GENESIS-Online database from the German Statistical Office (`https://www-genesis.destatis.de/genesis/online`), and the ifo business cycle climate index (`http://www.cesifo-group.de`) The estimation sample comprises monthly observations from 1991:1 to 2010:5.

4.1.1 The Binary Recession Series

As previously discussed, as already pointed out by Burns and Mitchell (1946), an economic recession is characterized by a *widespread* and *synchronized* downturn in overall economic activity observable on a broad set of economic variables. The proper dating of economic expansions and recessions should therefore result from a multivariate approach which takes into account this fact. For the sake of expositional simplicity and in order to assess on a monthly basis and in a more timely fashion the occurrence of turning points in the German economy, however, in this paper a univariate business cycle dating approach is preferred, with the index of industrial production as the business cycle reference series, as also done in a large number of previous studies, see e.g. Anas et al. (2008) and Darné and Ferrara (2009). Indeed, as discussed in Fritsche and Stephan (2002, p.291), the use of the index of industrial production as a proxy for business cycle movements can be justified by the fact that industrial production is "much closer to the 'volatile' aggregates of GDP like investment and exports – which are at the heart of most business cycle theories". Furthermore, besides the fact that the index of industrial production is published on a monthly basis, what, as mentioned before, greatly enhances the timely account of the business cycle, this series is also much less prone to revisions than the (quarterly) GDP figures.

Specifically, in this paper the Bry and Boschan (1971) algorithm was employed, according to which a peak in the business cycle is identified when

$$\{y_{t-k} < y_t > y_{t+k}, \quad k = 1, \ldots, 5\}$$

while, analogously, a trough is assumed to take place when

$$\{y_{t-k} > y_t < y_{t+k}, \quad k = 1, \ldots, 5\}.$$

where y_t is the two-month moving average of the German index of industrial production – the business cycle reference series.[5] Furthermore, as an additional censoring rule for the identification of recessionary periods and thus for the generation of the binary recession indicator series b_t, following Harding and Pagan (2002) a *triangle approximation to the cumulative movements* approach was pursued in order to measure the "severity" of an economic downturn j – and by extension the eventual occurrence of a recession –, which is specifically defined as

$$S_j = 0.5 \times Deepness_j \times Duration_j,$$

[5]Given the high volatility of monthly data, it is usual in the turning points dating literature to "smooth" the underlying business cycle reference series among other things to avoid potential outliers biases.

where the *duration* are the number of months between peak and trough of the economic downturn considered (according to the NBER definition of a recession as a *significant decline in economic activity* [of] *more than a few months*), and

$$Deepness_j = |y_p - y_t|/y_p,$$

with y_p and y_t are the respective values of the index of industrial production at the corresponding peak and trough, see Anas et al. (2008). A recessionary period was identified when $S_j < 0.005$, as there is no consensus on the reference minimum duration and deepness of recessions (Darné and Ferrara, 2009, p.5).

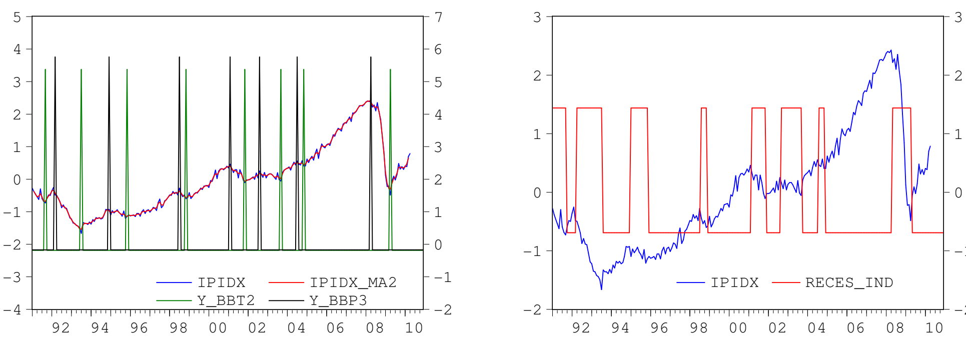

Figure 1: German industrial production, business cycle peaks and troughs calculated on the basis of the BB algorithm and related binary recession indicator.

Figure 1 illustrates the relationship between the underlying industrial production series and the resulting binary recession indicator series generated by the Bry and Boschan (1971) algorithm.

4.1.2 Macroeconomic Indicators

For the empirical analysis of this paper a variety of macroeconomic and financial variables were considered. Concerning the subset of variables which are supposed to reflect the development of the real side of the economy, besides the index of industrial production, the following indicators characterized by not being subject to data revisions were chosen: the open vacancies in the productive sector, the domestic and foreign orders received by the industrial sector, as well as the ifo business sentiment indicator (all variables as month-to-month % changes).

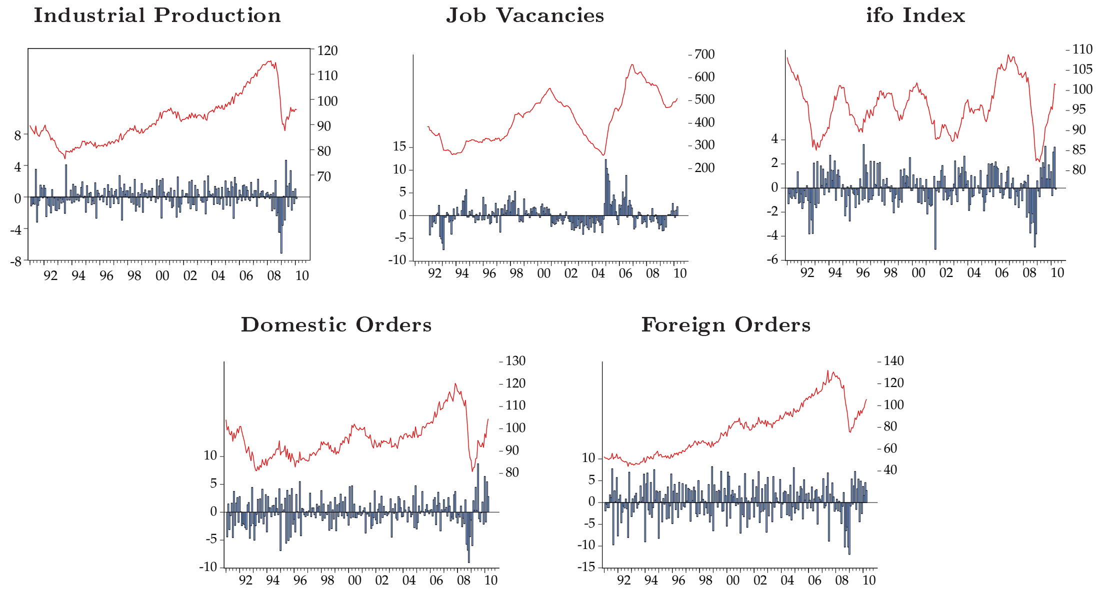

Figure 2: Macroeconomic Indicators: Industrial production index, job vacancies, foreign and domestic orders received by the productive sector, and ifo business sentiment index. Sources: Deutsche Bundesbank, DESTATIS, ifo Institute.

4.1.3 Financial Indicators

Concerning the financial indicators employed in this paper, these were selected as to represent a broad dimension of the financial markets. On the one hand, following Bernanke (1990) and Friedman and Kuttner (1992) the spread between average corporate bond yields of all maturities traded and the average yield of public securities was used, as well as the the growth rate of the CDAX price index in order to incorporate the German stock markets developments.

Furthermore, along the lines of Stock and Watson (1989), Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), and more recently Kauppi and Saikonnen (2008) and Nyberg (2009), the yield spread between the long-term and the short-term interest rate – was included in the general set of regressors. More specifically, alternative dynamic probit specifications using the 1-, 2-, 3-, 5- and 10-year yield (calculated by the Svensson's method) spreads to the three-month EURIBOR were estimated in order to address the uncertainty about which yield spread has the "best" prediction power, among other reasons which will be discussed in detail below. Furthermore, the short-term interest rate was also included in

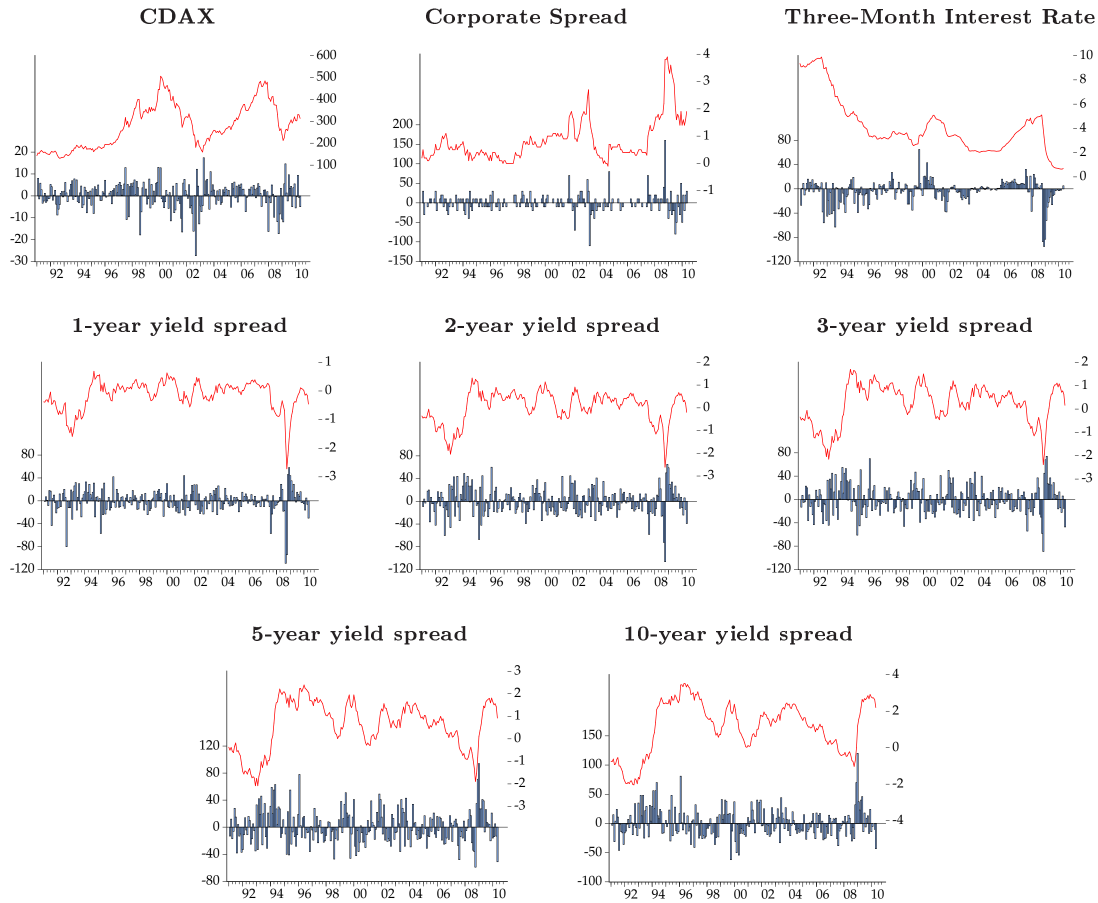

Figure 3: Financial Indicators: CDAX, Corporate Spread, Three-Month Euribor and yield spreads of different maturities. Source: Deutsche Bundesbank

the set of regressors. In this respect, Ang, Piazzesi and Wei (2006) show, using a dynamic factor model, that the two principal factors of the term structure at all traded maturities, which in their study account for 90% of the variation of the whole term structure, are highly correlated with the short-term interest rate, and the 10-year yield spread. Additionally, Wright (2006) shows that probit models with the yield spread of the 10-year T-bond to the three-month T-bill *and* the short-term three-month T-bill interest rate outperforms probit specifications using only the yield spread in the MSE sense. Table 1 summarizes the descriptive statistics of the whole set of explanatory variables.

In order to avoid eventual multicollinearity problems which may arise due to the strong correlation between the yield spreads of different maturities, as previously mentioned alter-

Table 1: Descriptive Statistics of Macroeconomic Indicators

	Sample: 1991m1 – 2010m2, Obs: 217								
	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
DEIPIDX	92.38	92	115.3	76.4	9.74	0.69	2.75	17.89	0.00
JOBVAC	418.82	415	659	259	107.75	0.35	2.03	13.04	0.00
DOM. ORDERS	84.55	83.6	135.5	53.6	18.84	0.65	2.72	16.11	0.00
FOR. ORDERS	84.55	83.6	135.5	53.6	18.84	0.65	2.72	16.11	0.00
YC1Y	3.87	3.61	9.47	0.72	1.77	1.06	4.52	61.31	0.00
YC2Y	4.05	3.89	9.11	1.27	1.65	1.03	4.39	56.20	0.00
YC3Y	4.26	4.15	8.88	1.66	1.56	0.94	3.97	40.78	0.00
YC5Y	4.63	4.48	8.47	2.29	1.44	0.74	3.07	19.65	0.00
YC10Y	5.21	4.96	7.96	3.21	1.33	0.51	2.09	16.92	0.00
CDAX	84.06	75.69	06.08	31.29	98.53	0.33	2.06	11.89	0.00
CRP_SPRD	0.84	0.6	3.9	-0.1	0.76	1.91	7.12	285.24	0.00

native dynamic probit models underlying the (invariant) set of explaining variables given by the industrial production index, the job vacancies, the ifo business sentiment index, the CDAX price index (all in % month-to-month changes), the corporate spread and the three-month EURIBOR, and alternatively the 1-, 2-, 3-, 5- and 10-year yield spreads (to the three-month EURIBOR) were specified and estimated. In the following the automatized model specification procedure is discussed.

4.2 Model Specification

As widely acknowledged, in any regression analysis the econometrician faces a trade-off between the cost of searching for the best specification in terms of statistical significance – or overall fit or prediction power – and the inference cost resulting from statistically insignificant variables. In order to avoid the latent problem of choosing an arbitrary model specification based on an ad-hoc selection of lagged values – and of the explaining variables in general – each alternative dynamic probit specification was estimated using on the one hand a general-to-specific, as well as a specific-to-general approach.

In the general-to-specific selection procedure (see Campos, Ericsson and Hendry (2005)), the explanatory contribution of each lag of each explanatory variable was tested using a redundant variables Likelihood Ratio (LR) test, with the LR statistic computed as

$$LR = -2(\mathcal{L}_R - \mathcal{L}_U)$$

where $\mathcal{L}_{\mathcal{R}}$ and $\mathcal{L}_{\mathcal{U}}$ are the maximized values of the (Gaussian) log likelihood function of the unrestricted and restricted regressions.[6] In the specific-to-general model selection procedure, in contrast, the added explanatory value of an additional lag of each explaining variable was tested using an omitted variables Likelihood Ratio test, where under the H_o the coefficient of the additionally added variable (lag) is not significant.

In a second step, using the estimated recession probabilities resulting from the different dynamic probit regressions, following Timmermann (2006), an equal-weighted average of these individual estimates (and forecasts) was computed in order to obtain a single recession probability series. Indeed, as recently pointed out also by Aiolfi, Capistrán and Timmermann (2010), the use of a combination of different forecasts is superior to the use of single forecasts as it may help to reduce the negative effects of model instability and increase the robustness of the estimation results.

4.3 Estimation Results

4.3.1 In-Sample Evaluation

In the following the in-sample fit of the dynamic probit regressions estimated over the entire sample period, i.e. 1991:1 – 2010:5 is discussed. To start let us focus on the dynamic probit specifications obtained by the *general-to-specific* (denoted by a G), and the *specific-to-general* (denoted by a S) approaches previously discussed for 1-, 2- and 3-month ahead forecasting summarized in Tables 2 – 4.

A variety of issues are worth to be highlighted. In the first place, at a more general level, the heterogeneity of the dynamic probit model estimations at all three analyzed forecast horizons corroborate the combinatorial approach pursued in this paper. Indeed, as it can be clearly observed in Tables 2 – 4, the significance level of the majority of variables (lags) is significantly affected by the specific yield spread included in the respective regression sets, on the one hand, as well as by the lag selection procedure (*general-to-specific* or *specific-to-general*) employed. There is, however, a certain "constancy" in the significance level of some variables (lags), which depends however on the underlying forecast horizon of the respective regressions. At the one-month-ahead forecast horizon, for example, the

[6] Under the H_o of this asymptotically χ^2 distributed test with one degree of freedom, the coefficient of a redundant variable (lag) is zero. A rejection of this test results in the conservation of the tested variable (lag) in the model specification.

third lag (relative to the end-point) of the job vacancies series and of the foreign orders received by the industrial sector, as well as the seventh lag of the CDAX monthly growth rate are significant across all probit specifications.

In the same sense, the ifo business sentiment index does not seem to have any statistical significance at the one-month ahead horizon when included among the sets of indicators employed in this paper, as well as the binary recession indicator series and the short-term interest rate. Furthermore, the inclusion of the (growth rate of the) business cycle reference series (the index of industrial production) seems to be valid from the statistical point of view, at least in some probit specifications. Also worth highlighting is the fact that the statistical significance of the different yield curves seems also to be affected by the variables (lag) selection procedures, as well as the corporate spread series and the series of the domestic orders received by the industrial sector.

In contrast to the one-month-ahead forecast specifications, in the two-month-ahead forecast regressions the binary recession indicator series (at the ninth lag) is statistically significant in all specifications, as well as (various lags of) the CDAX price index. In contrast, while both job vacancies and foreign orders (the variables with the highest statistical "constancy" in the previous case) does not seem to have any predictive power at the two-month-ahead forecast horizon, the opposite seems to hold for the corporate spread, which coefficients are statistically significant in eight of ten specifications. Also interesting is the fact that, in contrast to the previous case summarized in Table 2, in the two-month-ahead forecast regressions the ifo business sentiment index is statistically significant on four out of ten specifications.

Finally, the most remarkable fact concerning the estimation results of the three-month-ahead forecast specifications is the fact that in only one out of ten specifications the yield spread (specifically, the spread of the 5-year federal security rate to the 3-month EURIBOR) seems to have a statistically significant predictive power for recessions.

Table 2: Summary of Dynamic Probit Regressions, One-Month Forecast Horizon

	Sample: 1991:1 – 2010:5									
	EQ_YC1G	EQ_YC1S	EQ_YC2G	EQ_YC2S	EQ_YC3G	EQ_YC3S	EQ_YC5G	EQ_YC5S	EQ_YC10G	EQ_YC10S
Reces_Ind	-	-	-	-	-	-	-	-	-	-
Ipdix	-	3, 4, 5	-	3, 4	-	3, 4	-	-	-	3, 4, 5, 6
Dom.Orders	-	3, 4, 5	-	7	-	-	-	-	-	3, 4, 5
For.Orders	3, 4	3	3	3, 4, 5	3	3, 4	3	3, 4	3	3, 4
Job.Vac.	3	3	3	3	3	3	3	3	3	3
ifoidx	-	-	-	-	-	-	-	-	-	-
Crp_sprd	-	-	3	-	3	7	3	-	-	-
CDax	7	4, 6, 7	3, 4, 6, 7	7	3, 4, 6, 7	3, 6, 7	3, 4,6	3, 6, 7	4, 6, 7	4, 6, 7, 8
Euribor 3M	-	-	-	-	-	-	-	-	-	-
YC1Y	3, 4	-	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
YC2Y	n.a.	n.a.	3	-	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
YC3Y	n.a.	n.a.	n.a.	n.a.	3	3	n.a.	n.a.	n.a.	n.a.
YC5Y	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	3	-	n.a.	n.a.
YC10Y	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	3	8
Pseudo-R^2	0.291	0.345	0.304	0.284	0.308	0.309	0.3148	0.279	0.303	0.399
SSR	30.993	28.750	29.716	30.274	29.571	29.834	29.345	30.701	30.390	26.085
Avg. Log-Likelihood	-0.441	-0.407	-0.432	-0.444	-0.430	-0.429	-0.426	-0.448	-0.432	-0.373
AIC	0.945	0.924	0.946	0.971	0.942	0.958	0.934	0.960	0.929	0.892
SC	1.054	1.109	1.085	1.110	1.081	1.128	1.072	1.068	1.037	1.139
HQC	0.989	0.999	1.002	1.027	0.998	1.027	0.990	1.004	0.973	0.992

Table 3: Summary of Dynamic Probit Regressions, Two-Month Forecast Horizon

	Sample: 1991:1 – 2010:5									
	EQ_YC1G	EQ_YC1S	EQ_YC2G	EQ_YC2S	EQ_YC3G	EQ_YC3S	EQ_YC5G	EQ_YC5S	EQ_YC10G	EQ_YC10S
Reces_Ind	9	9	9	9	9	9	9	9	9	9
IPIDX	-	-	-	-	-	-	-	-	-	-
Dom.Orders	4, 5	-	4, 5	-	4, 5	-	4, 5	-	-	7
For.Orders	-	-	-	-	-	-	-	-	-	-
Job Vac.	-	-	-	-	-	-	-	-	-	-
IFOIDX	-	4, 5	-	5	-	-	-	-	4, 5	4, 5
CRP_SPRD	4	7, 9	-	9	4	9	7, 9	9	7, 9	-
CDAX	4,...,9	4, 6,...,9	6,...,9	4,...,9	4,...,9	6,...,9	4, 6,...,9	4, 6, 7	4, 6,...,9	4, 7, 9
Euribor 3M	-	-	4	-	-	-	-	9	-	9
YC1Y	4	-	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
YC2Y	n.a.	n.a.	-	-	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
YC3Y	n.a.	n.a.	n.a.	n.a.	-	8	n.a.	n.a.	n.a.	n.a.
YC5Y	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	4	8, 9	n.a.	n.a.
YC10Y	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	4	-
Pseudo-R^2	0.296	0.301	0.343	0.284	0.298	0.348	0.311	0.358	0.335	0.348
SSR	30.559	31.645	29.253	30.274	30.650	28.314	30.425	28.938	29.654	28.670
Avg. Log-Likelihood	-0.433	-0.429	-0.403	-0.444	-0.431	-0.398	-0.423	-0.393	-0.408	-0.400
AIC	0.972	0.955	0.887	0.971	0.969	0.876	0.953	0.865	0.921	0.879
SC	1.153	1.121	1.023	1.110	1.151	1.011	1.135	1.000	1.103	1.015
HQC	1.045	1.022	0.942	1.027	1.043	0.930	1.027	0.920	0.995	0.934

Table 4: Summary of Dynamic Probit Regressions, Three-Month Forecast Horizon

	Sample: 1991:1 – 2010:5									
	EQ_YC1G	EQ_YC1S	EQ_YC2G	EQ_YC2S	EQ_YC3G	EQ_YC3S	EQ_YC5G	EQ_YC5S	EQ_YC10G	EQ_YC10S
Reces_Ind	8	9	8	10	8	10	8	10	8	10
IPIDX	-	-	-	-	-	-	-	-	-	-
Dom.Orders	9, 10	-	7,...,10	-	7,...,10	-	7,...,10	-	7,...,10	-
For.Orders	-	-	7,...,10	-	7,...,10	-	7,...,10	-	7,...,10	-
Job Vac.	-	-	-	-	-	-	-	-	-	-
IFOIDX	-	5	-	5	-	5	-	5	-	5
CRP_SPRD	7, 9	7, 10	9	-	9	7	9	10	9	10
CDAX	5,...,10	6,...,10	5,...,8	6, 7, 10	5,...,8	6, 7, 10	5,...,8	10	5,...,8	10
Euribor 3M	5	10	5	10	5	10	5	10	5	10
YC1Y	-	-	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
YC2Y	n.a.	n.a.	-	-	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
YC3Y	n.a.	n.a.	n.a.	n.a.	-	-	n.a.	n.a.	n.a.	n.a.
YC5Y	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	-	8	n.a.	n.a.
YC10Y	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	-	-
Pseudo-R^2	0.356	0.366	0.362	0.328	0.362	0.328	0.362	0.351	0.362	0.327
SSR	26.757	26.996	28.783	29.314	28.783	29.314	29.345	28.160	28.783	29.530
Avg. Log-Likelihood	-0.395	-0.388	-0.391	-0.412	-0.391	-0.412	-0.391	-0.398	-0.391	-0.412
AIC	0.905	0.874	0.923	0.886	0.923	0.886	0.923	0.858	0.923	0.878
SC	1.101	1.040	1.165	0.991	1.165	0.991	1.165	0.964	1.165	0.968
HQC	0.984	0.941	1.021	0.928	1.021	0.928	1.021	0.901	1.021	0.914

When compared with the outcomes of previous related empirical studies, among the just discussed estimation results a particularly interesting one is not only the corroboration of the predictive power of stock price developments respecting future economic activity already documented by Harvey (1989), Stock and Watson (1999), and recently by Haltmeier (2008), but also that in contrast the predictive power of the yield spread (irrespective the underlying maturity) does not seem to be as statistically significant as commonly thought.

Let us know focus on the advantage of the combination of the different estimated probabilities at the one- two- and three-month-ahead forecast horizon illustrated in Figure 4. As it is clearly observable, while by and large the estimated recession probabilities of all

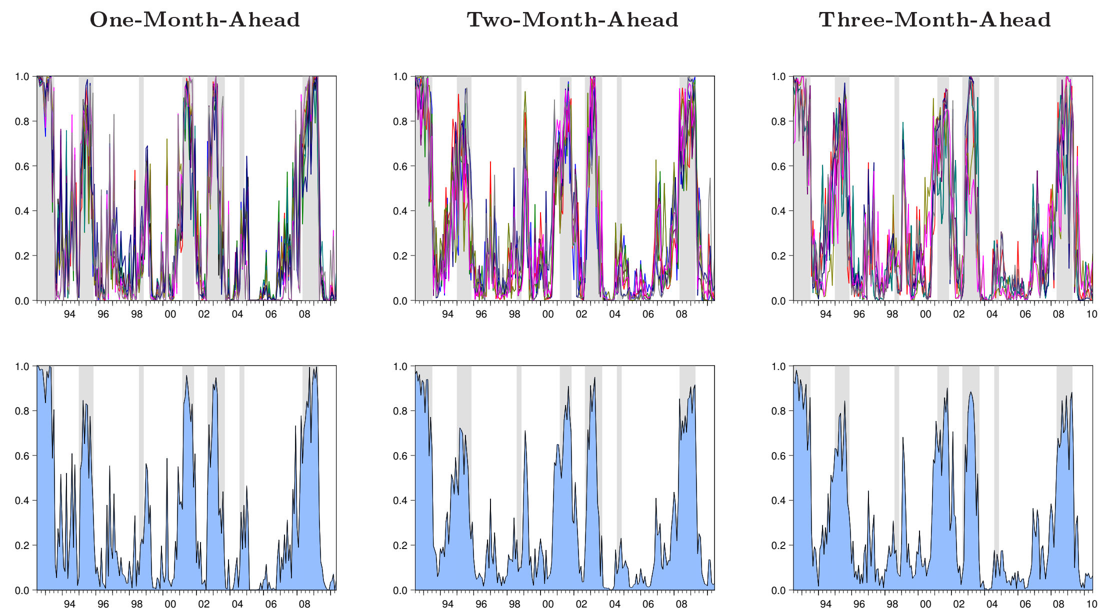

Figure 4: In-Sample Fit of Estimated and Average Recession Probabilities, One- Two- and Three-Month Forecast Horizon

probit specifications feature a similar pattern, there are some periods where the range of estimated probabilities becomes particularly high. This is particularly important in middle ranges of the interval [0 – 1], where the signal threshold of a recession might be set.

In order to assess in a more formal manner the capability of the probit regression, as well as of the averaging approach also pursued here, to deliver accurate signals for the occurrence of a recession, the percentage of Type I and Type II errors for a success cut-off value of 0.5 are computed.

Table 5 highlights the value-added of combinating the estimated probabilities of the alternative probit specifications resulting from the important forecast accuracy range of the different probit specifications.

Table 5: Expectation-Prediction Evaluations of Probit Regressions, Sample: 1991:1–2010:5

	Dep=0	Correct	% Correct	% Incorrect	Dep=1	Correct	% Correct	% Incorrect
One-Month-Ahead Forecast Horizon								
EQ_YC1G	151	138	91.39	8.61	69	36	52.17	47.83
EQ_YC1S	151	139	92.05	7.95	69	45	65.22	34.78
EQ_YC2G	151	141	93.38	6.62	69	43	62.32	37.68
EQ_YC2S	151	139	92.05	7.95	69	38	55.07	44.93
EQ_YC3G	151	141	93.38	6.62	69	45	65.22	34.78
EQ_YC3S	151	139	92.05	7.95	69	42	60.87	39.13
EQ_YC5G	151	138	91.39	8.61	69	47	68.12	31.88
EQ_YC5S	151	141	93.38	6.62	69	36	52.47	47.83
EQ_YC10G	151	136	90.07	9.93	69	45	65.22	34.78
EQ_YC10S	151	135	89.40	10.60	69	46	66.67	33.33
Two-Month-Ahead Forecast Horizon								
	Dep=0	Correct	% Correct	% Incorrect	Dep=1	Correct	% Correct	% Incorrect
EQ_YC1G	157	145	92.36	7.64	69	40	57.97	42.03
EQ_YC1S	158	143	90.51	9.49	69	36	52.17	47.83
EQ_YC2G	157	144	91.72	8.28	69	42	60.87	39.13
EQ_YC2S	158	143	90.51	9.49	69	40	57.97	42.03
EQ_YC3G	157	144	91.72	8.28	69	41	59.42	40.58
EQ_YC3S	160	144	90.00	10.00	69	47	68.12	83.41
EQ_YC5G	157	143	91.08	8.92	69	39	56.52	43.48
EQ_YC5S	159	141	88.68	11.32	69	45	65.22	34.78
EQ_YC10G	158	144	91.14	8.86	69	41	59.42	40.58
EQ_YC10S	158	144	91.14	8.86	69	42	60.87	39.13
Three-Month-Ahead Forecast Horizon								
	Dep=0	Correct	% Correct	% Incorrect	Dep=1	Correct	% Correct	% Incorrect
EQ_YC1G	158	145	91.77	8.23	69	50	72.46	27.54
EQ_YC1S	158	149	94.30	5.70	69	50	72.46	27.54
EQ_YC2G	158	141	89.24	10.76	69	45	65.22	34.78
EQ_YC2S	158	146	92.41	7.59	69	43	62.32	37.68
EQ_YC3G	158	141	89.24	10.76	69	45	65.22	34.78
EQ_YC3S	158	146	92.41	7.59	69	43	62.32	37.68
EQ_YC5G	158	141	89.24	10.76	69	45	65.22	34.78
EQ_YC5S	158	141	89.24	10.76	69	44	63.77	36.23
EQ_YC10G	158	141	89.24	10.76	69	45	65.22	34.78
EQ_YC10S	158	146	92.41	7.59	69	40	57.97	42.03

Indeed, as the summary statistics in Table 5 clearly show, the accuracy in predicting especially the recessionary periods vary from correctly predicting 36 out of 69 recessionary periods (52.17 %) by EQ_YC1G to 47 out of 69 (68.12 %) by EQ_YC5G. Furthermore, it is also interesting to note that the forecast accuracy in predicting recessions of the different probit specifications varies across the forecast horizon: At the one-month forecast horizon EQ_YC5G has the highest forecast accuracy, at the two-month the specification with the best performance is EQ_YC3S, and at the three-month horizon are EQ_YC1G and EQ_YC1S.

4.3.2 Out-of-Sample Evaluation

In order to assess the out-of-sample forecasting performance of the estimated probit models, following Moneta (2005), the out-of-sample recession probability forecasts were computing under pseudo real-time conditions by performing the following steps: First, the different probit regressions were estimated over the 1991:1 to 2008:4 period in order to have a good starting estimation of the parameters. Then, the probability of recession at a given month ahead was estimated and its value recorded. After adding one more month to the estimation period and dynamically re-estimating each time the different probit regressions, the procedure was repeated. At the end a series of out-of-sample estimated probabilities over the period 2008:5 to 2015:5 was obtained.

To evaluate the out-of-sample forecasting performance of an estimated probit model $\mathcal{M}$, three common measures of forecast accuracy (see e.g. Rudebusch and Williams (2009)) were employed: the mean absolute error (MAE)

$$MAE(\mathcal{M},h) = \frac{1}{T}\sum_{t=1}^{T}|P^{\mathcal{M}}_{t|t-h} - b_t|,$$

the root mean squared error (RMSE)

$$RMSE(\mathcal{M},h) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(P^{\mathcal{M}}_{t|t-h} - b_t\right)^2},$$

and the Theil Inequality Coefficient

$$Theil = \frac{\sqrt{\sum_{t=T+1}^{T+h}(P^{\mathcal{M}}_{t|t-h} - b_t)^2/h}}{\sqrt{\sum_{t=T+1}^{T+h}(P^{\mathcal{M}}_{t|t-h})^2/h} + \sqrt{\sum_{t=T+1}^{T+h} b_t^2/h}},$$

which, as it is widely known, lies in the interval $[0, 1]$, where 0 represents a perfect fit and 1 no explanation whatsoever.

Table 6: Out-of-Sample Forecast Evaluation under Pseudo-Real-Time Conditions (Starting In-Sample: 1991:1 – 2008:4, End of Out-of-Sample Forecast Sample: 2010:5)

	One-Month-Ahead Forecast Horizon					
	RMSE	MAE	Theil Coeff.	Bias-Prop.	Var-Prop.	Cov-Prop
PBJYC1G	0.383772	0.255278	0.299297	0.022444	0.101335	0.876221
PBJYC1S	0.411707	0.261427	0.324788	0.006079	0.060161	0.933760
PBJYC2G	0.358714	0.241156	0.280374	0.028134	0.127961	0.843906
PBJYC2S	0.408974	0.253033	0.316078	0.010942	0.052036	0.937022
PBJYC3G	0.358571	0.237072	0.274341	0.042636	0.119664	0.837700
PBJYC3S	0.373911	0.233910	0.290208	0.016187	0.077039	0.906774
PBJYC5G	0.350216	0.227172	0.281616	0.007150	0.111999	0.880851
PBJYC5S	0.386357	0.236175	0.286534	0.042764	0.062769	0.894467
PBJYC10G	0.381184	0.259424	0.319729	0.000432	0.118414	0.881154
PBJYC10S	0.382520	0.229142	0.297668	0.007958	0.054946	0.937096
PBJ_AVGPRB	0.366629	0.243379	0.290155	0.016135	0.112654	0.871211
	Two-Month-Ahead Forecast Horizon					
	RMSE	MAE	Theil Coeff.	Bias-Prop.	Var-Prop.	Cov-Prop
PBJYC1G	0.384110	0.241515	0.272958	0.110177	0.087597	0.802226
PBJYC1S	0.434622	0.308749	0.308748	0.125084	0.129933	0.744983
PBJYC2G	0.409514	0.241466	0.316326	0.005812	0.037005	0.957182
PBJYC2S	0.494657	0.365132	0.379818	0.028112	0.081645	0.890242
PBJYC3G	0.366069	0.203961	0.264960	0.054707	0.044049	0.901244
PBJYC3S	0.549586	0.448528	0.412291	0.055240	0.119305	0.825455
PBJYC5G	0.380490	0.241352	0.295324	0.017283	0.079082	0.903635
PBJYC5S	0.489915	0.409061	0.391167	0.041380	0.202847	0.755773
PBJYC10G	0.389032	0.230161	0.302403	0.006360	0.047559	0.946081
PBJYC10S	0.389032	0.230161	0.301026	0.057612	0.185249	0.895407
PBJ_AVGPRB	0.396237	0.307629	0.313513	0.049801	0.223362	0.726837
	Three-Month-Ahead Forecast Horizon					
	RMSE	MAE	Theil Coeff.	Bias-Prop.	Var-Prop.	Cov-Prop
PBJYC1G	0.445173	0.308718	0.337620	0.035310	0.082437	0.882253
PBJYC1S	0.478278	0.314176	0.346346	0.044266	0.041671	0.914063
PBJYC2G	0.462682	0.320099	0.331114	0.082176	0.080101	0.837724
PBJYC2S	0.443074	0.289889	0.318688	0.067686	0.062245	0.870069
PBJYC3G	0.422619	0.277716	0.306185	0.072581	0.077246	0.850173
PBJYC3S	0.415345	0.252762	0.278480	0.177193	0.069804	0.753003
PBJYC5G	0.424416	0.263994	0.329951	0.007183	0.045901	0.946916
PBJYC5S	0.451451	0.333082	0.359826	0.018417	0.113081	0.868503
PBJYC10G	0.431982	0.259346	0.320943	0.022028	0.032833	0.945139
PBJYC10S	0.431982	0.259346	0.322512	0.082527	0.161568	0.915474
PBJ_AVGPRB	0.421642	0.300249	0.317931	0.056963	0.121307	0.821731

As Table 6 clearly summarizes, the specified dynamic probit models, as well as the estimated probability series resulting from their combination seem to deliver not only statistically meaningful results and significant predictive power, but also feature good out-of-sample properties.

5 Concluding Remarks

As previously pointed out, the timely and accurate recognition of turning points in the business cycle is one of the most important, but also one of the most difficult tasks in macroeconomic forecasting. As a contribution along these lines of research, in this paper a practical econometric approach to the forecasting of recessions under real time conditions based on the combination of alternative dynamic probit regressions was presented.

The resulting dynamic probit regressions delivered a variety of important and interesting insights on the power of several macroeconomic and financial variables in predicting recessionary periods at different forecast horizons. Especially worthwhile to be highlighted again was in particular the predictive power of stock price changes at all analyzed horizons, on the one hand, as well as the contrasting result concerning the yield spreads of federal securities at different maturities.

There is, however, much more work to be undertaken. Accounting for nonlinearities, for example in the sense of a state-dependent predictive power of the explanatory variables, as well as the statistical comparison of the present approach with the performance of other econometric techniques seem promising research fields. We intend to pursue these and other issues in further work.

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